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Recipe for correcting the effect of mesoscale resolution on the estimation of extreme winds

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Abstract

Two statistical approaches are provided to estimate the smoothing effect due to mesoscale weather models' resolution, in terms of the peak factor. The first approach combines the effects of temporal and spatial resolutions to temporal effect. The second approach takes into account the difference in the mesoscale spectrum between simulated and observed winds, and its impact on the annual wind maxima distribution. The correction is aimed to bridge the gap between the models' resolution (tens of kilometers and hourly) to the upper limit of the meso- scale, namely, a few kilometers and approximately 10 min. Both approaches show reasonably good results in comparison with measurements from several sites.

Keywords: extreme winds, resolution effect, mesoscale range

1 Introduction

For winds simulated with mesoscale models, the variations in the mesoscale range are smeared because of spatial averaging and temporal resolution effects. This is reflected in the spectral domain as the low spectral energy level. This issue is illustrated in Figure 1, where for frequency $f > 2$ day^{-1}, the spectrum of the observed wind speed $S(f)$ follows $f^{-5/3}$, while the spectral energy from the wind speeds from various simulations has a steeper slope, with f^{-3}. The wind variation in the mesoscale range is important in contributing high wind cases and hence in the estimation of the peak effect.

In this paper, simulations from three different mesoscale models are used to examine the spectral behavior in the mesoscale range. The three models are: the regional atmospheric climate model HIRHAM5 (high Resolution limited area model and ECHAM, version 5, [1]), the Weather Research and Forecasting model WRF ([2]) and regional climate model REMO.

It is the intention of this paper to estimate the smoothing effect upon the extreme wind calculation induced by models' resolution, from a scale of 1 hour to 10 minutes, or equivalently, from tens of kilometers to a few kilometers. The estimates will be examined with 10-min measurements from several sites in Denmark and Germany.

The extreme wind, normally in terms of the 50-year wind, is often calculated with the statistical method the Annual Maximum Method (AMM)([3, 4]). In connection with this method, two approaches are provided here to estimate the effect of resolution on the annual maximum wind (U_{max}) in terms of the peak factor k_p, with k_p defined as

$$k_p = \frac{U_{max} - \overline{u}}{\sigma} \tag{1}$$

with $\overline{u}$ the mean wind speed and σ the standard deviation of the yearly time series.

In the following, the three meteorological models are briefly described in Section 2 and the two approaches are introduced in Sections 3 and 4, together with the estimated resolution effect. A Summary is given in the end in Section 5.

2 The atmospheric models and the spectra

The three models are often used in Northern Europe for wind energy applications. Table 1 lists the horizontal resolutions, simulation period and large forcing of the three models.

HIRHAM5 combines the dynamics of the numerical weather prediction model HIRLAM (version 7) and the physical parameterization schemes of the global climate model ECHAM5 (ECHAM version 5). The details can be found in e.g. [1] and [5].

The regional climate model REMO is a three dimensional hydrostatic atmospheric model. Details about the model set up can be found in [6, 7]. REMO was first nested with a horizontal resolution of 50 km using one-way nesting technique and again nested with a resolution of 10 km using a double nesting strategy.

The weather forecasting model WRF (version 3.1.1) setup uses standard physical parameterizations including Yonsei University planetary boundary layer scheme ([8]). The grid-nudging method is employed.

Outputs from the three models are all hourly.

In Figure 1, the spectra of wind speed at 10 m are from the HIRHAM5 simulations forced by ECHAM5 (HIRHAM5-ECHAM5) as well as forced by ERA40 (HIRHAM5-ERA40), the REMO simulations at 10 and 50 km resolutions and the WRF simulations at 15 and 45 km resolutions, all from the grid point closest to Horns Rev. The offshore site Horns Rev is chosen in order to avoid many issues such as surface heterogeneity and its consequence in the modeling, so that we can put our focus on the resolution issue.

The group of spectra is shown in Figure 1, with only the range $f > 1$ day^{-1} shown. Note, when making the spectra, the time series from the entire period for each data set is used. This means that the data from different models do not have the same period and length. We tested with each time series using different periods and length and found that this only affects the low frequency range while for $f > 2$ day^{-1}, there is almost no difference. In order to see the tail behavior, we focus only on the frequency range with $f > 1$ day^{-1}. Apparently, the four simulations, HIRHAM5-ECHAM5, HIRHAM5-ERA40, REMO 10 km and WRF 15 km, with spatial resolution ranging from 10 km to 25 km, all hourly values, provide similar spectral form for $2 < f < 12$ day^{-1}, with $S(f)$ following approximately f^{-3}, while the 50 km resolution REMO and 45 km resolution WRF simulations give much more significant smoothing effect, with $S(f)$ following approximately f^{-4}. Note, 2 day^{-1} is the Nyquist frequency of the large scale forcing.

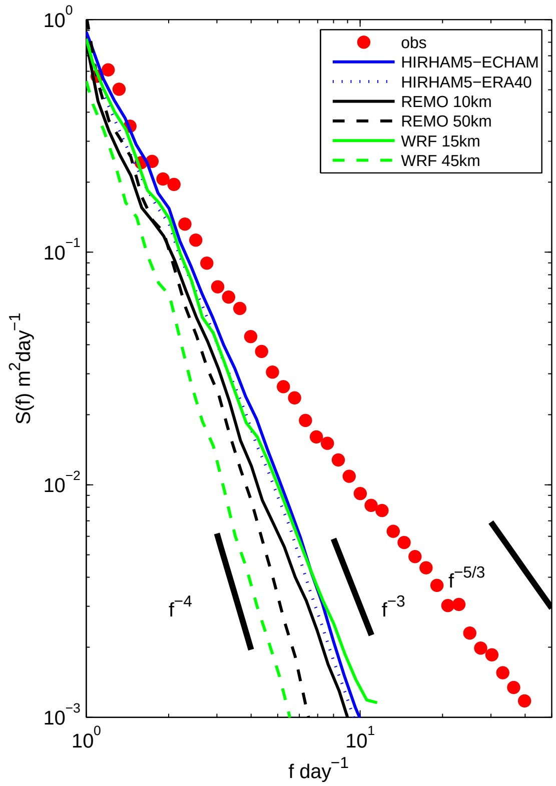

Figure 1: Spectra of wind speed at 10 m at Horns Rev from measurement as well as six various model simulations, see data details in Table 1.

Table 1: Model descriptions. All simulations give hourly outputs.

models	resolution	period	large scale forcing
HIRHAM5-ECHAM5	25 km	1961 - 1990	ECHAM5
HIRHAM5-ERA40	25 km	1961 - 1990	ERA40
REMO	50 km	1979 - 2003	ERA15 and ECMWF analysis
REMO	10 km	1979 - 2003	ERA15 and ECMWF analysis
WRF	45 km	1999 - 2009	NCEP reanalysis II
WRF	15 km	1999 - 2009	NCEP reanalysis II

3 Approach-I to estimate the resolution effect: Equivalent temporal averaging

In this approach, we try to combine the resolution effects of the simulated values due to spatial averaging and coarse temporal sampling rate or averaging into the temporal effect.

In [9], by assuming the wind time series a Gaussian process, the peak factor, denoted here as k_{p1} in this approach was derived as

$$k_{p1} = \sqrt{(1+\rho)\ln(\frac{N}{\pi}\sqrt{\frac{1-\rho}{1+\rho}})} \quad (2)$$

N is the number of 10 min values in a year. The autocorrelation coefficient of wind speed, ρ, for disjunctive sampling intervals or blocking averages, are given in [9]. With the disjunctive sampling rate (T_d) or the averaging time (T_a) increasing, ρ and N decrease and so does k_{p1} as well. Thus, the underestimation of U_{max} due to temporal resolution can be estimated.

The effect of temporal averaging on the spectral energy is shown in Figure 2. Here the data are 10-min winds measured at Horns Rev, corrected from 15 m to 10 m using logarithmic wind law and Charnock's formula for roughness length. For $f > 2$ day^{-1} the spectrum from the 10 min values follows approximately $f^{-5/3}$, but at longer running-averaging time, it drops with a steeper slope with f. The spectra from the various models are plotted together in Figure 2 in different symbols. The simulated data are instantaneous values but saved every 1 hour, and at the same time, it is spatially smoothed over an area of 25 km by 25 km. As a result, take the HIRHAM-ECHAM as an example, it follows the spectrum where $T_a \approx 2$ hours. The smoothing effect is calculated as $SE_T = 1 - k_{p1,T_a}/k_{p1,10min}$.

From Figure 2, we can approximate the spatial averaging and the disjunctive sampling effect for HIRHAM-ECHAM to an averaging time of about 2 hours and thus get $SE_T = 12.3\%$. SE_T for $T_a = 2$ h were calculated from observed 10 min wind speed at 10 m from several observational sites using Equation (1) and they are 10% at Horns Rev, 9% at Sprogø, 12% at Tystofte, 11% at Kegnæs, 11% at Jylex and 14% at FINO. Seemingly, through Equation (2), reasonable estimation of the resolution effect can be obtained, which is also the conclusion from [9].

The drawback of this method is that sometimes it is difficult to fit a spectrum with a combined spatial and temporal smoothing effect into a temporal smoothing spectrum. Then a rather large uncertainty is expected, as can be seen in Figure 2. For the REMO simulated winds, the spectrum corresponding to 10 km resolution is distributed across $T_a \sim$ 2 to 5 hours and that for the 50 km across $T_a \sim 3$ to 5 hours, thus corresponding to SE_T in an even broader range about 12.5% to 17% and 15% to 17% respectively. For the WRF simulated winds, the spectrum is distributed across $T_a \sim 2$ to 3 hours for the 15 km resolution data and across $T_a \sim 4$ to 5 hours for the 45 km resolution data, corresponding to SE_T in the range of 12.5% to 15% and 16.5% to 17%, respectively. This suggests that the characteristics of the spectra from the REMO simulated winds result in larger uncertainty than the HIRHAM5 and WRF simulated winds when using this approach.

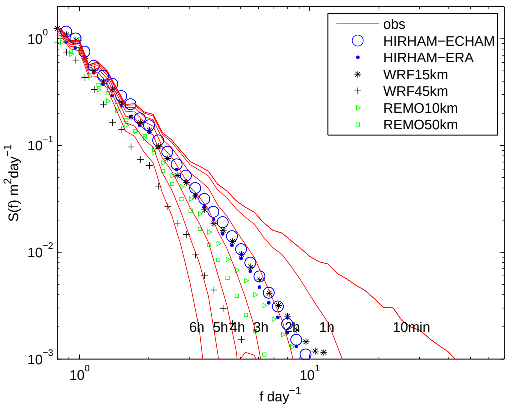

Figure 2: Spectra $S(f)$ as a function of frequency f. The curves are from observations of averaging time $T_a = 10$ min, 1, 2 and 6 hours. The other symbols show the modeled spectra from the various models. All values are at 10 m at the site Horns Rev.

4 Approach-II to estimate the resolution effect: Spectral correction

In this second approach, the resolution effect is estimated by taking into account of the different spectral tails.

Let the extreme value distribution follow $F = \exp(-\lambda T_0)$, where T_0 is the period, λ is the rate of occurrence and it is calculated as

$$\lambda = \int_0^\infty P(u,\dot{u})|\dot{u}|d\dot{u} \approx \frac{\sigma_{\dot{u}}}{\sqrt{2\pi}} P(u) \tag{3}$$

with $P(u)$ the probability of u. For a Gaussian process,

$$P(u) = \frac{1}{\sigma_u}\sqrt{2\pi}\exp(-u^2/(2\sigma_u^2)) \tag{4}$$

Substituting Equation (4) into Equation (3) gives

$$\lambda = \frac{1}{2\pi}\frac{\sigma_{\dot{u}}}{\sigma_u}\exp(-\frac{u^2}{2\sigma_u^2}) \tag{5}$$

In the format of momentum, Equation (5) can be written as

$$\lambda = \frac{1}{2\pi}\sqrt{\frac{m_2}{m_0}}\exp(-\frac{u^2}{2m_0}) \tag{6}$$

with m_0 and m_2 the spectral moments defined as

$$m_j = 2\int_0^{2\pi f_h} \omega^j S(\omega) d\omega \tag{7}$$

where $S(\omega)$ is the power spectrum of the Gaussian process and $\omega = 2\pi f$, with f in day^{-1} . Normally, in Equation (7), $f_h \to \infty$, here according to the situation, f_h is less than 72 day^{-1}, i.e. the resolution is never finer than 10 min. Using $f_h \leq 72$ day^{-1} avoids the convergence issue of Equation (7) if the tails having slopes not less than -2. It is rather straightforward to find out f_h if it is known which temporal resolution T_a is needed; it is the Nyquist frequency of T_a, so that $f_h = 1/(2T_a)$. Thus, $f_h = 72$ day^{-1} is for 10 min values and $f_h = 12$ day^{-1} is for 1 hour values. For the maximum wind that happens once a year, $\lambda T_0 = 1$, together with Equation (6) it eventually gives

$$u_{max} = \sqrt{m_0}\sqrt{2\ln(\frac{1}{2\pi}\sqrt{\frac{m_2}{m_0}}T_0)} \tag{8}$$

Here, the time series u was subtracted from the mean value, so that $u_{max} = U_{max} - \overline{u}$. Equivalently, the peak factor k_p can be expressed as a function of the spectral moments.

$$k_p = \frac{U_{max} - \overline{u}}{\sigma} = \sqrt{2\ln(\frac{1}{2\pi}\sqrt{\frac{m_2}{m_0}}T_0)} \tag{9}$$

Thus, the peak factors with different spectral tails can be estimated. Obviously, the high frequency range contributes mostly to $\sqrt{\frac{m_2}{m_0}}$ and hence k_p.

A simple procedure is given below to demonstrate the resolution effect, SE, varying with spectra with four different tails as shown in Figure 3.

We take a power spectrum form for $f < 2$ day^{-1}:

$$S(f) = \frac{2T\sigma_{fit}^2}{1 + (2\pi T f)^2} \tag{10}$$

followed by the four tails with $f^{-5/3}$ (tail-1), f^{-2} (tail-2), f^{-3} (tail-3) and f^{-4} (tail-4), respectively, see Figure 3. By making a fit with Equation (10) to a spectrum, one gets the values for T and σ_{fit}. σ_{fit} is not sensitive to the four tails in the mesoscale range, so for simplicity's sake, same σ_{fit} is used for the four cases.

Let $k_{p,i}$, where i =1 to 4, stand for the peak factor estimated with the four spectral tail forms, at a

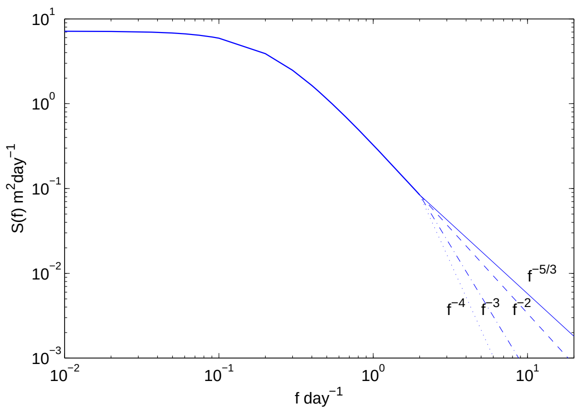

Figure 3: The spectrum model $S(f) = \frac{2T\sigma_{fit}^2}{1+(2\pi Tf)^2}$ for $f < 2$ day^{-1} and 4 different tails for $f > 2$ day^{-1}.

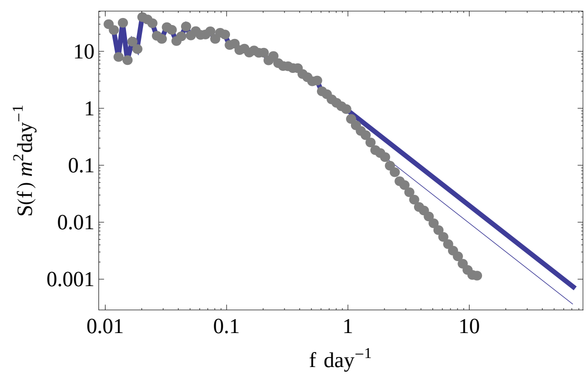

Figure 4: Modification of the spectrum of the hourly simulated wind speed (gray dots) by replacing the tail for $f > f_c$ with a spectrum of tail slope of $-5/3$ (the solid lines), in connection with the spectral approach. Here the thick line corresponds to $f_c = 1$ day^{-1} and the thin line corresponds to $f_c = 2$ day^{-1}.

certain temporal resolution. The smoothing effect, as the underestimation of k_p, is calculated as

$$SE = 1 - k_{p,i}/k_{p,0},\ i = 1, 2, 3, 4. \quad (11)$$

where $k_{p,0}$ is the reference peak factor with tail-1 and for 10 min values. In Figure 3, the start of different tails is set as $f_c = 2$ day^{-1}, being the Nyquist frequency of the large scale forcing for the mesoscale modeling. There is a slight increase of SE with the integral time scale T but it is very small. SE also varies with the start of the tail f_c. Understandably, the smoothing effect is larger if the tail starts at lower frequency, so that SE increases with decreasing of f_c.

For the simulated instantaneous values of 1 hour resolution, the estimate of SE corresponding to the different tails in comparison with the 10 min values with tail-1 is obtained in two steps: first, SE is calculated with $f_h = 12$ day^{-1} with different tails; second, SE is calculated with $f_h = 72$ day^{-1} and tail-1.

With $T = 0.8$ day, $\sigma_{fit} = 3$ ms^{-1}, $f_c = 2$ day^{-1} and $f_h = 72$ day^{-1}, if the 10 min time series corresponds to a spectral tail-1, the peak factor k_p can be calculated with Equation (9) and it is 4.98. The corresponding values of k_p from 10 min wind measurements at about 10 m from several observational sites are 4.46 (Horns Rev), 5.48 (Tystofte), 4.58 (Sprogø), 5.16 (Kegnæs), 5.81 (Jylex) and 5.39 (FINO). Seemingly, the model value for tail-1, 4.98, is a good approximate of the mean values from observations.

With $T = 0.8$ day, $\sigma_{fit} = 3$ ms^{-1}, $f_c = 2$ day^{-1} and $f_h = 12$ day^{-1} (corresponding to hourly values), the peak factors are: $k_p = 4.35$, 4.31, 4.22 and 4.16 for the four tails, respectively. Thus, SE of the instantaneous simulation values of 1 hour interval in comparison with the 10 min values are 12.7% (as a result of $1 - \frac{4.35}{4.98}$), 13.5%, 15.3% and 16.3% for tail-1, 2, 3 and 4, respectively.

In the absence of mesoscale modeling, i.e. if we estimate the smoothing effect on the global data only by removing the spectrum for $f > 2$ day^{-1}, SE is 27%, compared to 10 min values with tail-1.

When correcting the modeled values for the smoothing effect reflected on the spectral energy deficit to match the 10 min time series, the core of this approach is to replace the spectrum from modeled winds in the mesoscale range with a spectral slope of $-5/3$, and extend it to the frequency of 72 day^{-1}. This process is illustrated in Figure 4. This modified spectrum and the original modeled hourly spectrum provide two different m_2 as in Equation (9), and there the smoothing effect can be estimated.

The smoothing effect corresponding to the spectra from the simulated wind time series as shown in Figure 1 is thus calculated. The peak factor and the underestimation of it due to the energy deficit in the spectral tail are calculated and applied to the annual wind maxima through Eq. (1). The corrected mean annual wind maxima for the six simulations are listed in Table 2 as <U_{max}>. They are in very good agreement with the measurements: from the 10-min time series we obtain <U_{max}>=27.2 m/s. Here $f_c = 2$ day^{-1} was used but using $f_c = 1$ day^{-1} gives almost the same results.

5 Discussions and Summary

The resolution effects from space and time are related. However, the two effects are combined so that the method derived for correcting the temporal issues only in [9] is not sufficient. One of the approaches in this paper tries to approximate the combined resolution effects into a temporal one by fitting the spectrum to those of different averaging times. Although this empirical method is simple it has its limitations when the spectrum with this combined effect does not follow clearly a particular spectrum of certain averaging time.

The second approach given in this paper also assumes the time series are a Gaussian process. The occurrence rate, which for the Annual Maximum Method is once per year, is described in terms of the spectral moments. The temporal resolution is easily considered as the cutoff high frequency in the integration of the moments. The peak factor, k_p, can thus be estimated in terms of the spectral tails.

Different models would affect the estimate of the resolution effect of k_p through the shape of the spectral tail. For U_{max}, this effect also depends on the mean wind speed $\overline{u}$ and the standard deviation σ, which are expected to differ for different models. We have selected a rather simple situation here, namely, offshore; $\overline{u}$ and σ are comparable in all model simulations. Larger discrepancy is expected for a land site in these parameters from models of different resolution, dynamics and physics, and also larger discrepancy in the estimation of the resolution effect.

Both approaches in this paper are based on the simple assumption that the time series are Gaussian process. During extreme wind conditions, this process has often been suspected to be over-simplified. But the good agreement between the corrected values and the measurements suggests that this is a reasonable assumption, at least for the cases studied here. One could also skip this statistical correction by simply improving the mesoscale simulation to match the 10 min resolution. In e.g. [10], it was shown that the mesoscale model WRF is capable of producing not only the mean and standard deviation of the 10 min wind speed but also a spectral slope of approximately -5/3, at a horizontal resolution of 3 km. However, a climatological simulation of such a resolution is very expensive. Nevertheless, the estimates of the peak factor and the smoothing effect based on the statistical approaches seem to fall in the variation range given by measurements from several sites in Denmark and Germany.

It is straightforward to calculate that, if we use the Annual Maximum Method for the 50-year wind U_{50} (see [3, 4, 11]), the underestimation in U_{max} will be the same as in U_{50}.

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Table 2: For the Horns Rev site, peak factor k_p, smoothing effect of k_p and the predicted mean annual wind maximum <U_{max}> using the spectral approach for measurements and simulations. $k_p(I)$: for the hourly modeled time series with their steep slopes as in Figure 1. $k_p(II)$: modified spectrum with a tail slope $-5/3$, $f_c = 2$ day^{-1} and $f_h = 72$ day^{-1}. $SE = 1 - k_p(I)/k_p(II)$.

variables	OBS	HIRHAM5		REMO		WRF	
		ECHAM5	ERA40	10 km	50 km	15 km	45 km
$k_p(I)$		4.18	4.17	4.13	4.10	4.17	4.07
$k_p(II)$	5.01	5.00	4.99	4.98	5.00	5.00	4.97
SE		16.5%	16.5%	17.1%	18.0%	16.7%	18.1%
<U_{max}> (m/s)	**27.2**	**26.6**	**25.5**	**26.5**	**26.5**	**26.6**	**25.4**

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